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An IoT-Aware Approach for Elderly-Friendly Cities

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ABSTRACT The ever-growing life expectancy of people requires the adoption of proper solutions for addressing the particular needs of elderly people in a sustainable way, both from service provision and economic point of view. Mild cognitive impairments and frailty are typical examples of elderly conditions which, if not timely addressed, can turn out into more complex diseases that are harder and costlier to treat. Information and communication technologies, and in particular Internet of Things technologies, can foster the creation of monitoring and intervention systems, both on an ambient-assisted living and smart city scope, for early detecting behavioral changes in elderly people. This allows to timely detect any potential risky situation and properly intervene, with benefits in terms of treatment's costs. In this context, as part of the H2020-funded City4Age project, this paper presents the data capturing and data management layers of the whole City4Age platform. In particular, this paper deals with an unobtrusive data gathering system implementation to collect data about daily activities of elderly people, and with the implementation of the related linked open data (LOD)-based data management system. The collected data are then used by other layers of the platform to perform risk detection algorithms and generate the proper customized interventions. Through the validation of some use-cases, it is demonstrated how this scalable approach, also characterized by unobtrusive and low-cost sensing technologies, can produce data with a high level of abstraction useful to define a risk profile of each elderly person.

INDEX TERMS Elderly, IoT, LOD, MCI, monitoring systems, risk detection, smart environments.

I. INTRODUCTION

The demographic transition that has characterized Europe and World in the last decades, has led to an ever-aging population. About 27.3 million people aged 80 and over were living in the European Union (EU) in 2016, about 7 million more than ten years ago. The growing share of elderly people in the EU (from 4.1% in 2006 to 5.4% in 2016) means that, in 2016, one in every 20 persons living in the EU was aged over 80 years. The ageing of the population is, at least partly, the result of an increasing life expectancy together with the contemporary reduction of births. This is deeply changing European societies, with great effects on the younger generations' social expectations and new needs arising from the presence of a high number of elderly people. One of the

main problems of this new society is surely the assistance to elderly persons, i.e. people with disabilities due to ageing related functional and cognitive declining, i.e. frailty or Mild Cognitive Impairment (MCI).

MCI is an intermediate stage between the expected cognitive decline of normal aging and the more-serious decline of dementia. It can involve problems with memory, language, thinking and judgment that are greater than normal age-related changes. Attention to these individuals' problems has led to a remarkable research in the field of geriatrics, but above all to the development of new customized service models. The aim of these actions, as recommended by the World Health Organization (WHO) in its aging report, is to improve the health and quality of life of the elderly, in order to develop

and maintain functional ability, which allows for well-being in the elderly regardless of the presence of pathologies.

In a Smart City vision, the citizens activities are not limited to their houses; they live in a real community. Health care is important for citizens in general and, in particular, for the elderly. Smart Cities aim to address elderly people needs through transversal topics, such as housing, social participations health care, community support services, leisure, and culture, in order to make Smart City environment more elderly-friendly. In this sense, Information and Communication Technologies (ICTs) will enable this integration into home and urban environment where elderly people live, improving their quality of life, while increasing efficiency and reducing costs. In this perspective, the European Union promotes and funds research projects with the aim of encouraging industry to develop technologies to improve elderly's quality of life at home (AAL - Ambient Assisted Living). Smart cities need the latest ICT technology and its services to create a better sustainable and cost efficient environment.

In this context, the Internet of Things (IoT) [1], [2], with its advanced technologies, could be the way to guarantee better life conditions for the elderly, as well as to monitor their health through the development of innovative AAL solutions [3], [4]. One of the key elements of such monitoring systems is their unobtrusiveness, meaning that they should be able to detect the desired parameters without interfering with user's activities. To this purpose, suitable parameters for monitoring user's behavior are his/her positioning in indoor and outdoor spaces, his/her body motility ability and his/her interaction with the surrounding environment, especially at home. In this respect, the recent advancements in unobtrusive sensors in general, and in particular in mobile and wearable devices are a significant support.

This paper presents the work partially done within the City4Age¹ project and it describes the first two layers of the architecture used to collect and manage data related to elderly people and their daily activities, both in indoor and outdoor environments. These data are then used by system's upper layers for the detection phase, aimed at recognizing behavioral changes in the elderly and eventually trigger proper interventions. In particular, this work briefly introduces the main concepts involved in the modelling of the data capturing phase, where all low-level technological details are hidden with a quite high level of abstraction, avoiding that the whole system handles raw data with uncertain interpretations. Then, it describes in detail the Personal Data Capturing System, used to unobtrusively collect data related to elderly people. This capturing layer exploits innovative IoT technologies to create an unobtrusive, low-cost and low-power sensing infrastructure that abstracts the heterogeneity of physical devices and communication technologies. Another important component presented in this work is a data management architecture, called Data Store and Management System, that combines a high-performance REST application programming

interface (API) and a Linked Open Data (LOD) API. The REST API allows to easily manage large quantities of data, while the LOD API maps the information in the database to OWL, providing semantic meaning to the stored data and making them easier to share. Finally, an extensive validation of the above components has been carried out, including both low-level and high-level use cases, with particular focus on the Madrid pilot site of the City4ge project.

The paper is structured as follows. In Section II presents a brief overview of the state of the art about low-level sensing and middleware technologies at Smart City technologies level, including also an overview of similar research projects. The City4Age project is briefly described in Section III, including the adopted approach for data modeling. Section IV introduces the proposed system, with the architectural details about the Personal Data Capturing System and the Data Store and Management System deeply explained in Section V and VI, respectively. Section VII describes a low-level validation of the PDCS-DSMS interaction, focused on the watching TV use case, while in Section VIII, the high-level validation within the Madrid pilot is reported. Finally, in Section IX a feature-based qualitative comparison between the City4Age project and some other similar research projects is reported, showing how the City4Age platform fulfils several requirements of the Smart City context.

II. RELATED WORK

A. HARDWARE AND SOFTWARE TECHNOLOGIES

The Internet of Things (IoT) paradigm has become more and more important in World population's life because it is able to guarantee daily used tools and devices connectivity to the Internet, providing useful information to third parties and helping to create smart environments.

However, to create these environments it is necessary to have a hardware (sensors, actuators, devices, etc.) and software (often called as middleware) infrastructure. This infrastructure will capture data produced by users and send it to the services where they will be managed, processed, and stored.

Different reasons are given in the literature to justify the use of middleware. For example, [5] states that middleware is necessary because of: (i) the difficulty of defining and enforcing a common standard among all the devices of the environment; (ii) the need of a common abstraction/adaptation layer; (iii) the need of an Application Programming Interface (API), which will hide some details of the process to third parties. The paper offers a comparison of the state of the art of different middlewares, analyzing their characteristics (e.g. portability, device management, interoperation, context awareness, etc.).

Several authors have created examples of middlewares for smart environments. Those middlewares manage both sensor information and actions for a given reaction to those events. For example, Hossain *et al.* [6] present a middleware to generate alerts for dangerous situations perceived by diverse sensors in an intelligent environment. Ji *et al.* [7] present a

¹<http://www.city4ageproject.eu/>, <http://www.city4ageinsight.org/>

cloud-based car parking middleware that helps university students find the best car parking slot. Gómez-Goiri *et al.* [8] present a semantic framework which provides interoperability between two different devices using Triple Spaces and implementing a discovery process that uses the concept of semantic data. An alternative approach manages context information and splits it into a peer-to-peer network of context producers and context consumers to create an efficient reasoning process that can model the information in OWL² and share it over the Web [9].

Using ontologies for smart environment modelling has been extended in the research community. Latfi *et al.* [10] proposed an ontological architecture for a Telehealth Smart Home and developed prototype ontologies. Klein *et al.* [11] proposed a context ontology for ambient middleware as part of the European Union SOPRANO funded project [12]. They claimed that ontologies will be used as a central reference document for SOPRANO middleware.

Following that trend, Chen *et al.* present the concept of *Semantic Smart Homes* [13] as an extension of the current Smart Home in which data, devices and services are given well-defined meaning using a custom middleware. The main objective of the presented middleware is to have data within and across semantic homes defined and linked in a way that it can be used for more effective discovery, processing, automation, integration and reuse across various applications.

Some other approaches, like [14], create a framework to connect mobile devices (PDA, Smartphone) to intelligent environments to allow these devices to act as universal remote controllers and interact with different IoT devices. Krylovskiy *et al.* [15] present an implementation of microservices architecture to build Smart Cities using an IoT platform with the aim of increasing city's energy efficiency at district level. Azzara *et al.* [16] make an overview of the middleware solutions targeted in Wireless Sensor Networks which allows to interconnect large scale applications with programs that needs to manage each different IoT device. The scenario allows the creation of intelligent sensor network technologies and creates applications targeted to the Smart City scenario. A similar approach can be found in [17].

All those approaches show the importance of having a middleware that implements the needed operations to resolve different type of critical processes. The middleware is one of the central parts of current IoT infrastructure. It improves its value and creates large and scalable projects.

The approach proposed in this work presents a complete system to extract data from citizens of a big city and use middleware to build behavioral and clinical information to be stored in a cloud based database. The central core repository contains a centralized Linked Open Data system to share the most suitable data to third parties, allowing external programs to consume data and create new tools that can improve the citizens' lives.

B. SOFTWARE ARCHITECTURES FOR ELDERLY CARE SYSTEMS

While there exist several initiatives for providing remote elderly monitoring by using technology, in recent years, the approach to merge the Smart Cities view with IoT technologies has emerged, representing a common natural evolution of the purposes of both.

Some projects, focused on elder health monitoring, have appeared initially in 2013, such DIET4Elders,³ mainly focused on improving the quality of life by means of an appropriate healthy lifestyle based on diets, or NITICS,⁴ more focused on emergencies. This initial stream focused on specific solutions within the Smart Cities paradigm. At this stage, the main domains of services provided by the smart city were identified and some evidence of the necessity of new adapted services for elderly were already identified. Among these concerns, public transport could stand out as one of the recurring worries among the elderly population. As an example, it is worth to mention the report made by [18] which concluded to put bus services to the main supermarkets as requested by New Yorkers in the top of 59 resulting initiatives. The variation to holistic models that seek to postulate general approaches has resulted in an absence of solutions in the Smart Cities dedicated to elderly population during the last years, finding few exceptions. However, so far, no other project similar in objectives and nature to City4Age has been carried out. Similarities on certain technologies are obviously found but the inclusion of the Smart Cities open data to the elderly monitoring and the approach of the usage of different technologies is far from the up to date state of the art. In order to give a more practical approach, for the present study, it has been tried to focus current solutions from the final user perspective, like already done in other similar studies [19].

In this context, there exists an increasing trend calling for using wearable technology for monitoring elderly activity, sometimes requiring a huge investment on wearables (an extensive review is reported in [20]). Even if this solution adoption provides a wider range of specialization, including a variety of sensors such as IMU, GPS and connectivity hardware, the City4Age approach focused mainly on enhancing the usage of low cost mobile device. Smartphone provides that hardware and it is feasible for the proposed solution and makes use of everyday devices that additionally are familiar for a large portion of elderly population. The computational power and storage capabilities of the device allow performing different tasks in order to filter and sanitize the incoming data. This implies, not only attempting to remove extreme or out of sense values coming from the hardware, but also improving the acquisition of data by allowing a contextualization of the incoming data, pre-processing, statistics gathering and finally, cloud storing. The main advantage of not requiring an ad-hoc hardware for the monitoring is, apart from flexibility, the extensibility of the software solution. It is supported by

²<https://www.w3.org/TR/owl-features/>

³<http://www.diet4elders.eu/en>

⁴<http://www.aal-europe.eu/projects/nitics/>

the theory of evidence, a generalization of Bayesian inference postulated by [21] and extended by [22] on sensor data fusion prior to semantic notation. It is also a recommended practice for the acquisition of data in Smart Cities [23]. This opens a new scope of passive monitoring capabilities eased by the Smart Cities open data services such the public transportation information. By properly configuring a software solution, a smartphone can recognize whether the device is indoor or outdoor, or whether the user is using the public transport; hence, not limiting but also being improved the monitoring solution while operating outdoors. This solution is also combined with a GPS Location Based monetization. As long as the software solution runs on an OS including Google Services, such as Maps, then it is possible to dynamically configure, label and store different *Points Of Interest* (POIs) and gather metrics and statistics of the user's behaviors on a semantical level without any human intervention (apart of the initial configuration process). The result is a more reliable, robust, extensible and cheaper solution for elderly monitoring with a less complicated deployment and setup.

The current state of the art of IoT applied to elderly health-care includes different domains:

- Health: Related to monitoring medical parameters, heart rate, medication, fitness, degree of activity and sleep;
- Cognitive abilities: Memory, orientation, pattern recognition, etc.;
- Nutrition: Related to monitoring weight, diet or water consumption;
- Safety: Fall detection, behavioral change detection, posture recognition, etc.;
- Localization: Object location, indoor positioning, outdoor monitoring;
- Socialization: depression, social relationships, communication, etc.

The approach used within the City4Age Madrid pilot is to gather anonymous information related to almost all of the previous categories. With an appropriate set of metrics to gather, it is possible to infer high level conclusions that relate among others. As an example, by monitoring the localization of a user, it is possible to be aware as well of the degree of socialization of that certain user and also, the degree of physical activity.

III. CITY4AGE PROJECT DESCRIPTION

City4Age is a Horizon2020 research and innovation project with the goal of enabling age-friendly cities [24]. The project aims to create an innovative framework on ICT tools and services that can be deployed by European cities in order to enhance the early detection of risk related to frailty and MCI, and provide personalized intervention that can help the elderly population to improve their daily life promoting positive behavior changes. It also includes six pilot sites to test the outcomes of the research, which are located in Athens (GR), Lecce (IT), Birmingham (UK), Madrid (ES), Montpellier (FR) and Singapore. Fig. 1 shows the City4Age logical architecture [25], where the leftmost part deals with

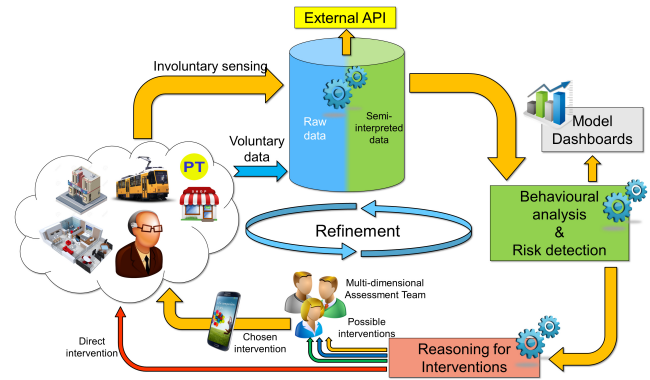


FIGURE 1. City4Age platform architecture.

the unobtrusive detection of elderly behavior patterns during their everyday life, in indoor and outdoor contexts, also at a city-wide scope. Collected data are then stored in a central repository, which acts as a data source for novel behavioral analysis and risk detection algorithms (the rightmost block). This step produces a list of possible customized interventions for each subject, which can be directly administered to the elderly or after the evaluation by a multidimensional assessment team. The smartphone plays a central role in this architecture, acting in many cases as a gateway for data transmission and as a terminal for interventions.

In each phase of the project, a particular attention has been given to the elderly people, trying to satisfy their needs. From a data collecting perspective, unobtrusive sensing technologies have been preferred, in order to not hinder elderly users during their daily life activities and to not require a frequent interaction with them.

One of the main overall achievements of the project is the definition of a set of geriatric factors (GEFs) and geriatric sub-factors (GESs) as quantitative indicators of the MCI/Frailty risk associated to a given elderly person. This risk model derives from the multidimensional analysis of the most commonly used tools in current geriatrics practice, that measure MCI and frailty based on behavior and human activities monitoring. Table 1 shows a partial list of the defined GEFs and GESs. The magnitude of GEFs and GESs result from the aggregation of data with a lower level of abstraction produced by a large set of sources. Therefore, in order to address issues related to heterogeneous data sources, low level technologies, semantic interpretation and so on, the City4Age project has defined the notion of Low-level Elementary Actions (LEAs). A LEA is the finest grain atomic information used to detect elderly people's behavior. It catches start/stop events of user basic actions, including additional information about time and position of the action that is being taken. All this information is formatted as the so-called Common Data Format (CDF), i.e. a JSON data object used to exchange data and information with a uniform and shared meaning hiding all technological low-level details, and sent to the upper layer of the City4Age Platform.

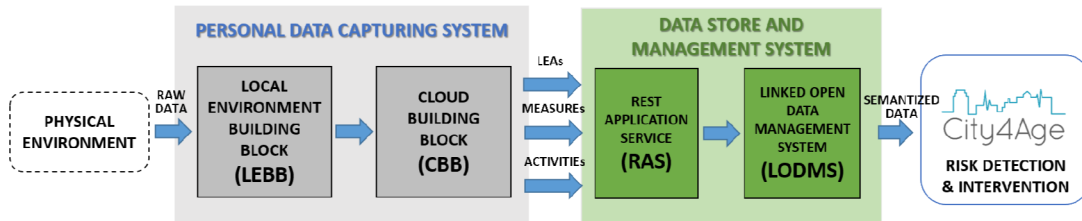


FIGURE 2. System architecture of the personal data capturing system (PDCS) and the data store and management system (DSMS).

TABLE 1. Excerpt of GEFs and GESs list.

Geriatric Factors	Geriatric Sub-factors
Motility	Walking, Climbing stairs, Still/moving, Moving across rooms
Basic activities of daily living	Bathing and showering, Dressing, Self-feeding, Going out
Instrumental activities of daily living	Ability to cook food, Housekeeping, Laundry, Phone usage, New media communication, Shopping, Transportation
Socialization	Paying/receiving visits, Attending senior centers, Attending other social places
Cultural engagement	Visiting cultural or entertainment places, Watching TV, Reading
Environment	Quality of housing, Quality of neighborhood
Health – Physical	Falls, Weight, Weakness, Pain, Appetite, Exhaustion, Quality of sleep, Visits to doctors, Visit to health related places
Health – Cognitive	Abstraction, Attention, Memory, Mood

LEAs can be grouped in the following macro-categories:

- **Person LEAs:** related to information about user’s motility, like standing, moving, walking, etc., or for collecting data about the usage of smartphone for calling and the number of visits payed or received;
- **Home LEAs:** concerning user position inside the house; the usage of home appliances and furniture, like fridge, TV, washing machines, cabinets, etc.; ambient parameters, like temperature, humidity, noise, etc.;
- **City LEAs:** for tracking user position inside monitored places in the city (shops, offices, pharmacies, etc.) and in outdoor city spaces (streets, parks, etc.); for tracking the interaction of user with public transportation systems, etc.

LEAs are collected as soon as they happen and they are sent to the storage layer for further elaboration, as explained above. Within the City4Age project, the concept of Measure has been introduced as a daily indicator that synthesizes a large set of occurrences of a given LEA. In fact, by analyzing all LEAs related to entering and exiting of the user in a given room, it can be computed how many times the user went to bathroom (as an example) in a day and the average time of permanence. These are typical examples of Measures, generated on a daily basis, that make sense from a geriatric point of view to assess changes of behavior relevant for MCI/Frailty detection. On the basis of these daily Measures,

GEFs and GESs indicators can be computed and the risk profile of each elderly person can be defined with a monthly interval. A well-defined and shared vocabulary of LEAs and Measures labels has also been defined as a deliverable of the project, with the aim of providing a common language for all low-level data producers.

IV. PROPOSED ARCHITECTURE

This work describes part of the general architecture defined in the context of the City4Age project, for the unobtrusive data collection from a heterogeneous sensing infrastructure. In particular, it deals with the so-called Personal Data Capturing System (PDCS) and Data Store and Management System (DSMS), shown in Fig. 2 [26], [27].

The main task of the Personal Data Capturing System is to collect raw data from sensors spread in the physical environment (independently of both their specific technologies and communication protocols) and process them to produce LEAs and Measures to be sent to the Data Store and Management System. The PDCS is composed of two main logical blocks. The Local Environment Building Block (LEBB) provides a modular set of software components (generally installed on smartphones or embedded devices acting as gateways), which are able to communicate with different sensing technologies according to the respective standards and protocols, in a uniform way. This capability abstracts the heterogeneity of the physical devices and provides a high degree of expandability to include upcoming technologies. The LEBB core logic translates raw data into LEAs and sends them to the Cloud Building Block (CBB). It is in charge to complete the data message object if any other information is missing, since the CBB has access to a wider range of information. Furthermore, the CBB performs other computations in order to calculate Measures based on the given LEAs. Finally, the CBB is in charge of sending both LEAs and Measures to the DSMS.

The Data Store and Management System (DSMS) integrates the data received from the IoT infrastructure using the Rest Application Service (RAS) and provides a semantic meaning following the Linked Open Data paradigm using the Linked Open Data Management Service (LODMS). This process also enriches the gathered data applying spatial and temporal knowledge eliciting rules, which improve the semantic knowledge and ease the inference and querying processes, so that data can be easily shared.

The PDCS is deployed locally in a private Cloud in each city, being adapted to the local IoT infrastructure. Only one deployment of the DSMS exists, integrating the data captured by all the local PDCS deployments.

V. THE PERSONAL DATA CAPTURING SYSTEM

The Personal Data Capturing System gathers large quantities of data from the physical environment through a sensing infrastructure, at home and city level. Four dimensions are considered for the data collection process. The first one is “User motility,” directly related to the Motility GEF: it collects data about the capability of the elderly people to actively make body activities, such as motion, rest, sleep, walking, etc. The second dimension is the “Indoor/Outdoor localization:” it collects data related to the position of the user inside a private or public indoor place, such as user’s homes or shopping malls, pharmacies, churches, etc., or data related to the position of the user in outside places, like streets, parks, etc. This information is used for the computation of several GEFs and GESs. The third dimension, the “User/Environment interaction,” dealing with data related to the user interaction with the surrounding environments, especially with home appliances (TVs, HVACs, etc.) and public services, for example public transportation, is used to feed various GEFs, like “Instrumental activities of daily living” or “Cultural engagement”. Finally, despite the lack of a corresponding GEF, the “Ambient parameters” dimension, concerning to quality of the living condition in indoor and/or outdoor environments, like temperature, humidity, luminosity, weather conditions. It can help in interpreting collected data and enhancing the risk detection algorithms.

Since several and heterogeneous technologies can be potentially involved in the process of gathering data for the categories listed above, the main rationale behind the City4Age approach has been to define a reference solution for each gathering sub-system. Each of them is fully compliant with the LEBB-CBB architecture and starts from the sensing requirements expressed by the six pilot sites being part of the City4Age project.

By analyzing all pilots’ scenarios, two main solutions are used as gateway for gathering data from the sensing infrastructure and sending them to a local platform for a first stage of elaboration. The first solution uses the smartphone, which interacts with physical devices mainly through BLE connection and relays data by using its cellular data connection. The second solution, instead, uses a wired home gateway, which receives data from the home sensing infrastructure and relays them through a DSL or cellular data connection. Both types of gateways implement the LEBB module inside them. In all cases, instead, the CBB is implemented in a (local or Cloud) server, locally managed by Pilots’ managers, which directly interact with the DSMS with the communication protocol described above.

The Cloud Building Block is the first layer of data aggregation provided by the City4Age architecture. It is implemented as a Cloud-based service for each City adopting the

City4Age approach. It is managed by local administrators and it deals with the collection and forwarding of LEAs and with the calculation of Measures to be sent to the Data Store and Management System. Although each Municipality is free to implement its own CBB service, the City4Age architecture has proposed the L-WoX and WoX [28], [29] frameworks as reference implementations of LEBB and CBB, respectively. However, L-WoX and WoX are not the focus of this work.

A. USER MOTILITY AND INDOOR-OUTDOOR LOCALIZATION

Taking into account the requirements of all City4Age pilots, it can be seen that the motility detection process is based on two main solutions: the use of wearable devices, like BLE wristband or smartwatch, and the use of the MEMS motion sensors available on the smartphone. In these cases, both public available Apps and APIs or custom Apps can be used.

Regarding the indoor home monitoring, instead, it is based on two main approaches, one based on BLE beacons interacting with smartphone or wristband, and one based on motion and contact sensors applied in rooms and on doors.

BLE beacons are also used to monitor indoor public places in the city, since this technique is more precise and reliable than using geo-located POIs, which does not provide the certainty that the elderly people is actually inside the place of interest.

Moreover, POIs definition and the interaction with smartphone’s GPS receiver, is the most adopted solution to track elderly people position in outdoor environment.

The innovative solution proposed by the City4Age project as a reference architecture for the User motility and Indoor/Outdoor localization sub-systems, is based on a low-cost prototypal wristband, associated with a smartphone, able to unobtrusively collect, in a seamless way, data related to both motility and localization topics. In fact, the wristband is equipped with 9-axis inertial sensors (accelerometers, gyroscopes, magnetometers) and with a BLE interface, which allows it to listen to BLE advertisements and to connect to a smartphone. In conjunction with the smartphone, it plays the role of the LEBB of the PDCS. In particular, the prototypal wristband, by exploiting its inertial sensors, is able to classify the body posture of the elderly by analyzing the collected data with a machine learning approach. The result of the classification is then sent firstly to the smartphone, by exploiting the BLE interface of the wristband, and then to the CBB, through the smartphone Internet connection, for further analysis. The BLE interface is also exploited by the Indoor Positioning service running on the wristband: it can read the information broadcasted by a beacon-based indoor positioning infrastructure (one beacon per each room) and, after calculating in which room the user is currently located by performing a classification algorithm based on RSSI, it sends this information to the smartphone and the CBB with the same mechanism illustrated above.

Typical outputs of this module are the BODY_STATE_START/ BODY_STATE_STOP LEAs indicating the

timestamp when the user enters and leaves a particular body state (i.e. still, walking, sleeping, etc.) and the POI_ENTER/POI_EXIT LEAs, indicating the location type and/or the GPS coordinates (by exploiting the GPS receiver of the smartphone [30]).

Data provided by these services help to identify elderly people behaviors and, above all, their variations, which may represent an early indicator of more severe conditions.

B. USER-ENVIRONMENT INTERACTION

Detecting how elderly people interact with their surrounding environment is not a trivial task, since several complex activities should be taken into account, both in indoor and outdoor contexts. For the purpose of this work, only the home environment is considered, because it is strictly related to specific GESs, like “Ability to cook food,” “Housekeeping,” “Laundry,” which can produce a lot of information about the physical and cognitive status of the elderly.

Several and heterogeneous technologies are involved in this task. For example, the activity of meal preparation can be inferred by using vibration, motion and contact sensors installed on furniture and tools (FURNITURE_OPEN/CLOSED LEAs), but also by monitoring when particular appliances are used, like oven, blender, coffee machine, and so on. Other GESs of instrumental activities of daily living GEF can be detected by monitoring home appliances; for example, the washing machine is linked with laundry, the vacuum cleaner with housekeeping, the TV with watching TV, etc. Therefore, by monitoring the activation and the power consumption of these electrical devices (which impact on the global power consumption of the entire house) it is possible to infer behavioral patterns, and their potential changes, of the inhabitants of the house. However, this detection should be as less unobtrusive as possible, both from a deployment point of view, and both from a usage point of view. Low cost of monitoring devices is also a valuable feature.

This work is based on a hybrid approach [31]: an unobtrusive smart power meter constantly measures the overall energy consumption. Then, it communicates these values to a Cloud-based software module for appliance disaggregation of devices having a well-defined power signature (like microwave oven, washing machine, fridge, etc.). In addition, in order to detect the usage of devices with low power consumption (for example TV or medical devices), especially when they are used at the same time of other appliances, one or more smart plugs are used. They detect if the attached load is on or off and send this information to the CBB for further elaboration. This module enhances power consumption data with data collected by other monitoring systems, for example the user motility and indoor positioning system so the process of user/environment interaction detection can be more accurate, trying to associate the operation of a device with the most probable user.

This approach foresees the installation, on the central power meter provided by the electric supply company, of an optical sensor that detects the blinking frequency of its LED,

used as a visual interface. Generally, such meter has two LED for providing real-time information on active and reactive power consumption: the upper LED indicates the active power consumption (1 blinking for Wh), whereas lower LED the reactive power consumption (1 blinking for varh).

The optical sensor can be installed for each LED and provides its digital output to a data acquisition and wireless transmission board, acting as LEBB. Each time the sensor detects the blink, it increases a counting variable. When the set time interval ends, the data acquisition board will send the counted LED flashes number to the CBB through one of the supported communication interfaces (Wi-Fi, Bluetooth Low Energy, GPRS, 3G/4G, etc.). The actual communication interface can be selected on the basis of the available home infrastructure.

By storing the resulting number from blinking counting into the microcontroller memory, every minute or every 30 seconds, as function of the specific user requirements, greater accuracy in determining the average consumed electrical power is obtained. On the CBB, a software module collects data for a time window of a day, and, after computing the real power consumption from number of blinks, tries to identify which appliances have been activated and de-activated during that period. Then, the proper APPLIANCE_ON and APPLIANCE_OFF LEAs are sent to the City4Age Platform.

As stated before, in order to identify a particular appliance’s usage, the LED blinking frequency is not sufficient; a certain number of smart plugs is needed. Smart plugs are simple electrical plugs, equipped with some electronics and a wireless communication interface, that are able to read the power consumption of the attached load and send this information to a remote server or to a paired smartphone app. Generally, smart plugs have a Wi-Fi or a BLE interface and often are provided with a proprietary smartphone app that allows to control the plug and monitor the consumption over the time. Some smart plugs provide also open APIs to communicate with, so customized applications can be created to not only monitor power consumption, but to detect when a particular device is used by the proper user. This feature has been exploited in this work. In fact, a customized smartphone app implementing the role of LEBB has been created. It periodically scans environment with the objective to find out the available smart plugs. Then, it establishes a connection with each of the discovered plugs and reads the current power consumption by exploiting the most suitable communication technology. After that identifies if the load is ON or OFF and finally sends this information (along with the current power consumption) to the CBB through the smartphone Internet connection (via Wi-Fi or 3G/4G).

During the configuration phase of this monitoring system, a census of the present appliances is performed by analyzing the number, the typologies and the location of electrical equipment inside the home environment. Subsequently, based on user requirements or habitual usage of household appliances by the elder, the system configurators define the minimum number of needed smart plugs, where to install

them and the type of appliances to connect. Furthermore, a database on the CBB contains all the available appliances, their consumption and the installed smart plugs with connected devices. In this way, the algorithm running on CBB, by analyzing data from LED-based monitoring system and from smart plugs, on the basis of updated database, will be able to establish the list of used appliances.

VI. THE DATA STORE AND MANAGEMENT SYSTEM

The data captured by the Personal Data Capturing System needs to be stored and managed in order to be later analyzed and consumed. To make this possible, a proper approach is to use a Cloud based storage system which allows a 24/7 access point to the IoT middleware. Each middleware deployment can send the data gathered from the citizens and have it stored securely for future analysis. However, having an external server is a source of data exposure or possible unauthorized access. All the stored data must be filtered and protected so only allowed third parties can access, thus guaranteeing the citizens' privacy.

The Data Store and Management System (DSMS) has been developed to fulfill the necessity of having a secure persistence storage in the Cloud. The gathered data from the IoT middleware is anonymized to prevent the citizens' identification and a set of access rules are enforced to ensure that only authorized third parties can query stored data. Thus, the DSMS covers two different scenarios: (i) allow the IoT middleware to have a secured channel to persist the data; (ii) allow the already stored data to be shared to third parties following the linked open data principles.

The DSMS offers a set of different tools to store, recover and share the acquired data using a set of different controls and filtering the most sensitive data. The proposed system is composed of two different software blocks: (a) A block called as a REST API, which is used as a primary source of data acquisition; (b) A block called as Linked Open Data Management System, which loads the stored data from database and, by giving it a semantic meaning, shares it over the web to be consumed by third parties.

Fig. 3 depicts the general architecture of the DSMS. The two blocks (represented in the left and right parts) are using the same technical core: a relational database. In this architecture, the relational database acts as the central point of the entire architecture to have the data stored securely. The reason of using a relational database rather than other solutions (NoSQL, Triple-Store, etc.) is based on the necessity of having a powerful, reliable and stable system that can hold a high number of requests from the different middlewares. The relational database is used to persist and secure the data gathered from the different IoT services.

A. REST APPLICATION SERVICE

The REST Application Service (RAS) is an API which allows to IoT middleware store the acquired data in the relational database. The aim of this software block is to manage the connections between different IoT middlewares, execute the

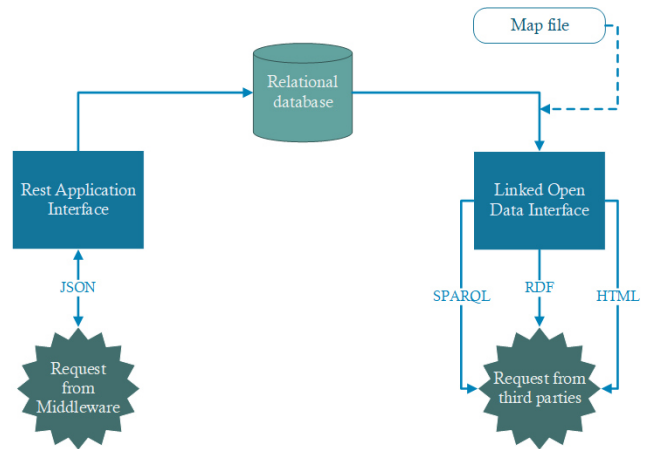


FIGURE 3. Architecture of the proposed system. The left part contains the REST Application service block, which acquires the needed data from IoT middleware. The right part contains the Linked Open Data block, which provides the needed endpoints to consume the stored data using three different endpoints.

needed toolsets to control the consistency of the data and execute the needed algorithms to persist all information into the database.

The RAS uses two different type of cypher algorithms to store the most sensitive and critical data. The first one is based on the bcrypt [32] library, which is used to hash the passwords of the users in the RAS. This process ensures that the stored passwords of the potential data consumers are secured. The second cypher algorithm is based in Advanced Encryption Standard (AES) [33] which is used to store citizens' sensitive information, like medical or personal measures.

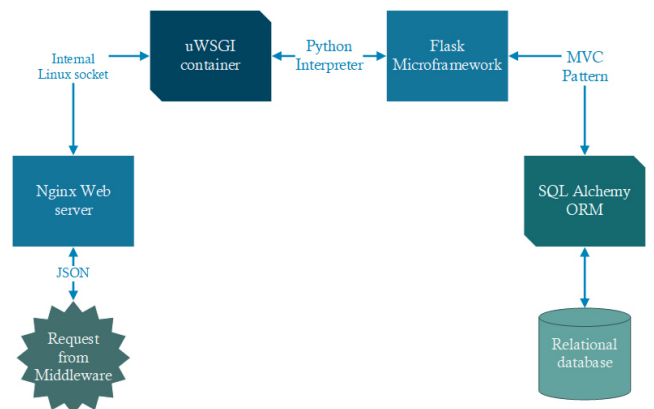


FIGURE 4. Schema of the REST Application Interface. In the figure it is possible to see the different technical technologies used to create this block. The workflow starts from requests from IoT middleware and finished in the relational database. Data can be sent or recovered at any moment.

Fig. 4 shows in more detail the RAS architecture. The RAS is build using a Web server (Nginx),⁵ a Web service (Flask)⁶

⁵<https://nginx.org/>

⁶<http://flask.pocoo.org/>

and a ORM (SQLAlchemy).⁷ The Web server handles middleware's connections and controls the connections between the Web Services and the requests. If a request is accepted by the web server then it sends to an internal socket between the uWSGI⁸ container and the server. This internal socket makes the role of a 'bridge' connection to inform the uWSGI container that there is a request. The uWSGI container recovers the request and executes the needed Flask microframework Python code to execute the algorithms that make possible the data transmission to the SQLAlchemy ORM. The ORM manages the interaction with the relational database in order to store or recover the needed data based on the received request.

The data acquisitions process is done through three different endpoints. Each of them are prepared to accept a set of defined data structure. The available endpoints are: *add_action*, *add_activity* and *add_measure*. The RAS allow different integration levels with the deployed IoT middlewares, depending on the needs and the requirements of each city. By allowing each city to select the abstraction level of the provided data, they can reuse the existing ICT infrastructure.

The *add_action* endpoint is used to store a set of LEAs, these actions are defined as everyday life basic actions, e.g. put the milk in the bowl, open the fridge, close a door, etc. The aim of storing these type of actions is to have a daily trace of users' performed actions and then to use them to recognize different type of activities. These activities are used to discover patterns and to predict possible mental diseases like Alzheimer, MCI, or physiological measures, like frailty.

The *add_activity* endpoint is used to store activities. An activity is a set of different LEAs, for example, "Make the dinner" could be an activity name that represents the needed LEAS to prepare a dinner (enter to the kitchen, open the fridge, turn on the over, etc.). This endpoint allows providing the activities directly to those cities with an already deployed Activity Recognition mechanism.

Finally, the *add_measure* endpoint is used to store a set of different type of citizen's measures. These measures could be from physiological measures to the number of visits to a defined place. They are ordered in a hierarchical set of geriatric factors and geriatric sub-factors. An example of this could be a 'motility' factor which contains a set of sub-factors like 'run' or 'climb stairs'. In addition, the IoT middleware's can extract the needed data by using another different endpoint that makes searches into the database.

Calling to each endpoint can be performed by using a client based data transfer program. The following lines contain an example of a CURL⁹ request command to the *add_action* endpoint to send a set of different LEAS using the JSON format structure (examples of this format can be seen in Section VII).

```
curl-u admin:admin-i-XPOST-
d@json_add_action_multiple.json
https://138.5.23.232:5000/api/0.1/add_action--
header"Content-Type:application/json"
```

The command sends a JSON file (*json_add_action_multiple.json*) which contains a list of LEA instances to the RAI. It also sends the needed user credentials to authenticate the user in the system and provide a security layer, which is described in Section VI-D.

B. LINKED OPEN DATA MANAGEMENT SYSTEM

The main objective of the Linked Open Data Management System (LODMS) is to provide a unified access point to the stored data to authorized third parties. For that purpose, we adopt the paradigm of Linked Open Data, creating insightful semantic information to be consumed by third parties. Some exemplary use cases could be the following: 1) a technology based company that needs to know some defined metrics for a given city to launch a new product based on certain citizen's needs; 2) the necessity of a city council to know which part of the population has an average growth of mental or motility diseases to approve some funds and create better placements or medical support (hospitals, senior centers and so on).

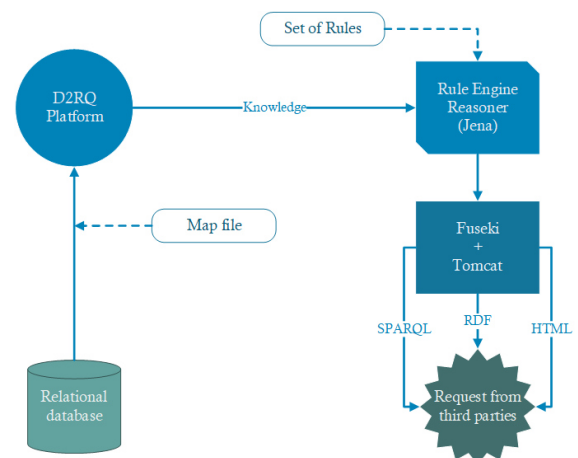


FIGURE 5. Schema of the Linked Open Data Management system. In the left part, the D2RQ program extracts the relational data from database and, by using a map file, it makes the needed conversion to semantic data. The right part, uses a rule based engine reasoner to create new statements based on spatio-temporal rules and then, it uses a web server called Fuseki to provide three different endpoints.

Fig. 5 depicts the architecture of LODMS which is divided into three different parts.

The first part, placed in the left, extracts the data from the relational database and converts it into semantic data. To achieve that, firstly it is necessary to design an Ontology that covers the context of the smart cities and the citizen behaviors and measures. Having the Ontology defined, the system uses a D2RQ¹⁰ platform which transforms the relational data into semantic data using a mapping process.

⁷<https://www.sqlalchemy.org/>

⁸<https://github.com/unbit/uwsgi>

⁹<https://curl.haxx.se/>

¹⁰<http://d2rq.org/>

This process requires a file called as “mapping.ttl” that contains a set of descriptors, which connects each relational database table and column with a class and property of the previously mentioned Ontology. In our terminology, we use the term *knowledge* to call the transformed semantic data.

The second part, placed in the center, uses a rule-based reasoning engine to apply a set of spatio-temporal rules to extract the implicit knowledge of the semantic data. To implement the rule engine reasoner, we use the well-known Apache Jena¹¹ framework. The rule-based reasoner, expands the *knowledge* loaded from the D2RQ platform to a desired direction and creates the needed matches into the semantic data to be consumed by potential third parties. We implement this *knowledge* inferring process due to the necessity of having natural relationships among entities in order to discover new data statements. The creation of new statements based on the rules is a periodical process that makes the semantic data more usable when the database information is updated or modified over the time.

The third part, placed in the right, uses a Resource Description Framework¹² (RDF) sever called as Fuseki.¹³ This server is a container inside a Web server, which in our approach has been implemented under the Apache Tomcat¹⁴ framework. The Fuseki server allows to share the loaded knowledge across the Internet and provides three different endpoints to allow third parties to obtain semantic data: 1) A SPARQL¹⁵ based endpoint to perform SPARQL-based queries; 2) A RDF-based endpoint to obtain loaded knowledge in RDF encoded file; 3) an HTML based interface that provides a graphical representation of the data and allows third parties to execute SPARQL based queries.

C. THE DATA MODEL

As it is explained in Section III the presented architecture uses a relational database as the back-bone of the architecture to store and manage all the data. Hence, it is important to make a representative model of how data should be stored in the database, as well as to define the best approach for efficient data insertion and extraction.

We decided to logically separate the stored data into two different database schemas: 1) The Activity Recognition schema (AR); 2) The Shared Repository schema (SR).

1) ACTIVITY RECOGNITION SCHEMA

The AR schema stores data related with citizen actions, activities and personal user accounts. This schema is used by an activity recognition system that uses an algorithm to discover activities based on a set of LEAs [34]. The schema contains different tables such as **Executed_Activity** table which stores the sent LEAs data of a citizen, **User_In_Role**

which stores the personal user accounts (account validation, anonymized information and so on), **Executed_Activity** table which defines what is the number of actions that contains an activity (MakeBreakFast contains different actions to make it), **CD_Action** the codebook of the different actions that can be stored in the repository (put the milk in the bowl, open the fridge) and **CD_Activity** the codebook of the different activities that are possible to be discovered in the context of a smart city.

2) SHARED REPOSITORY SCHEMA

The SR schema allows storing data related to medical measures of monitored citizens. This database is used by an integrated behavior recognition system and risk assessment to represent citizen’s anomalies. In addition, the data is visualized and classified using a graphical dashboard, where geriatricians can follow the evolution of some pre-defined meaningful measures related with MCI and frailty. Based on those measures geriatricians will be able to plan interventions for those citizens that present risky profiles. The schema contains different tables such as **Variation_Measure_Value** table which contains the values about the measures of a citizen over the time, **CD_Detection_Variable** which contains the codebook of possible detection variables that can be stored (Geriatric factors and sub factors.) and **Care_Profile** table which makes possible to have a status of a citizen and store if it is necessary or not perform an intervention when its health is inside a critical zone (for example, if a citizen is frail, fit or pre-frail).

D. APPLYING SECURITY MEASURES TO THE ARCHITECTURE

Viewing the proposed architecture, one of the most important concerns that appears in the project is to know how data is stored and what type of security measures are considered to protect the user’s privacy. Those two questions, are answered by implementing a set of security measures inside the project and making an efficient database design to decide which is the best place to store the acquired data.

Firstly, the system has a set of security measures in the REST Application Service to allow only authorized users to send or recover personal data from the system. These measures are based in HTTP-Auth¹⁶ identification and JSON Web Secured Tokens¹⁷ to send encrypted credentials and allow or deny the user’s requests. In addition, each authorized user in the system has a role-based access, thus it can only view or modify the data according to its permission level.

Secondly, all the user’s requests are protected using Secure Socket Layer (SSL) connections, with trusted signed certifications to ensure that every request to the API is encrypted and protected. The SSL connections creates an encrypted

¹¹<https://jena.apache.org/>

¹²<https://www.w3.org/RDF/>

¹³https://jena.apache.org/documentation/serving_data/

¹⁴<https://tomcat.apache.org/>

¹⁵<https://www.w3.org/TR/rdf-sparql-query/>

¹⁶<https://developer.mozilla.org/en-US/docs/Web/HTTP/Authentication>

¹⁷<https://jwt.io/>

tunneled channel to protect the communication between two machines and make the information unreadable.

Thirdly, as described previously in Section VI.A, the RAS uses two different encryption algorithms (bcrypt and AES) which makes stored data unreadable to external attackers. Only RAS contains the needed encryption and decryption algorithms to manipulate the stored data and make it readable or unreadable.

Fourthly, the Linked Open Data implementation contains a security tool called Apache Shiro that provides a set of security measures which restricts the access into the Fuseki server. This allows preventing external SPARQL injections from malicious attackers [35].

VII. LOW LEVEL VALIDATION

A. PERSONAL DATA CAPTURING SYSTEM VALIDATION

This Section aims to describe how the different sub-systems of the PDCS produce fine grain data that, once sent to the DSMS, can be composed by the upper layers with the aim of defining the behavioral profile of the elderly user. In particular, it will show how the User motility and Indoor-Outdoor Localization sub-system and the User/environment Interaction sub-system can support, as an example, the definition of the Watching TV GES. In this case, in fact, in order to state that the elderly is actually watching TV as a durable activity, it is necessary that, time by time, (i) the TV is switched on, (ii) the elderly is in the same room where the TV is located, and (iii) the elderly is in a still position. The lack of any of these conditions is sufficient to state that the elderly is not watching TV.

Let us suppose that the test environment is composed of the following sensing infrastructure. The house is equipped with a set of BLE beacons for indoor positioning (ContextBeacon Mini),¹⁸ the proposed prototypal smart meter placed on the electrical power meter, and a couple of smart plugs (Revogi SPB012)¹⁹ for detecting the usage of domestic appliances, like TV and washing machine. The elderly person, instead, is equipped with a wristband based on the SensorTag²⁰ for motility and indoor positioning detection, and with a smartphone acting as a gateway for data gathering and forwarding (LG G3).

In order to assess condition (i), the *User/environment Interaction* sub-system exploits the functionalities provided by the smart-plugs and the customized app to periodically check, every 5 minutes) the power consumption of the controlled TV, since it is a low-consuming device, often switched on contemporary to other more power consuming devices. When the TV is on, the smartphone app will send the LEA shown in Fig. 6.

The data for assessing condition (ii) is provided by the *Indoor-Outdoor Localization* sub-system. When the elderly person, wearing the prototypal wristband, moves within his/her house, at the moment when the software module

```

1. {
2.   "action": "eu:c4a:APPLIANCE_ON",
3.   "user": "eu:c4a:user:aaaaa",
4.   "pilot": "LCC",
5.   "location": "eu:c4a:Room:LivingRoom",
6.   "position": "40.359566 18.192550",
7.   "timestamp": "2017-10-20 18:08:41.013329",
8.   "payload": {
9.     "appliance_id": "68:c9:0b:17:e0:06",
10.    "appliance_type": "TvSet",
11.    "instance_id": 721
12.  },
13.  "rating": 1,
14.  "data_source_type": ["sensors"],
15.  "extra": {}
16. }

```

FIGURE 6. CDF of the APPLIANCE_ON.

```

1. {
2.   "action": "eu:c4a:POI_ENTER",
3.   "user": " eu:c4a:user:aaaaa",
4.   "pilot": "LCC",
5.   "location": "eu:c4a:Room:LivingRoom",
6.   "position": "40.359566 18.192550",
7.   "timestamp": "2017-10-
8.     20 18:02:22.013329",
9.   "payload": {
10.    "instance_id": 124
11.  },
12.  "rating": 0.8,
13.  "data_source_type": ["sensors"],
14.  "extra": {}
15. }

```

FIGURE 7. CDF of the POI_ENTER.

```

1. {
2.   "action": "eu:c4a:BODY_STATE_START",
3.   "user": " eu:c4a:user:aaaaa",
4.   "pilot": "LCC",
5.   "location": "eu:c4a:Room:LivingRoom",
6.   "position": "40.359566 18.192550",
7.   "timestamp": "2017-10-
8.     20 18:09:12.013329",
9.   "payload": {
10.    "state_type": "Still",
11.    "instance_id": 62
12.  },
13.  "rating": 0.8,
14.  "data_source_type": ["sensors"],
15.  "extra": {}
16. }

```

FIGURE 8. CDF of the BODY_STATE_START/STOP LEAs after the elaboration made by CBB.

running on the smartphone recognize a room change, it generates LEAs like the one shown in Fig. 7.

Finally, the *User motility* sub-system provides elements to assess condition (iii). The classification algorithm running on the wristband is able to recognize when the user is in a STILL position, and notifies this information to the related smartphone app, which, in turn, sends the LEA shown in Fig. 8.

¹⁸<https://www.easycontext.com/en/beacons/>

¹⁹<http://www.revogi.com/smart-power/smart-meter-plug-eu-2/>

²⁰http://www.ti.com/ww/en/wireless_connectivity/sensortag/

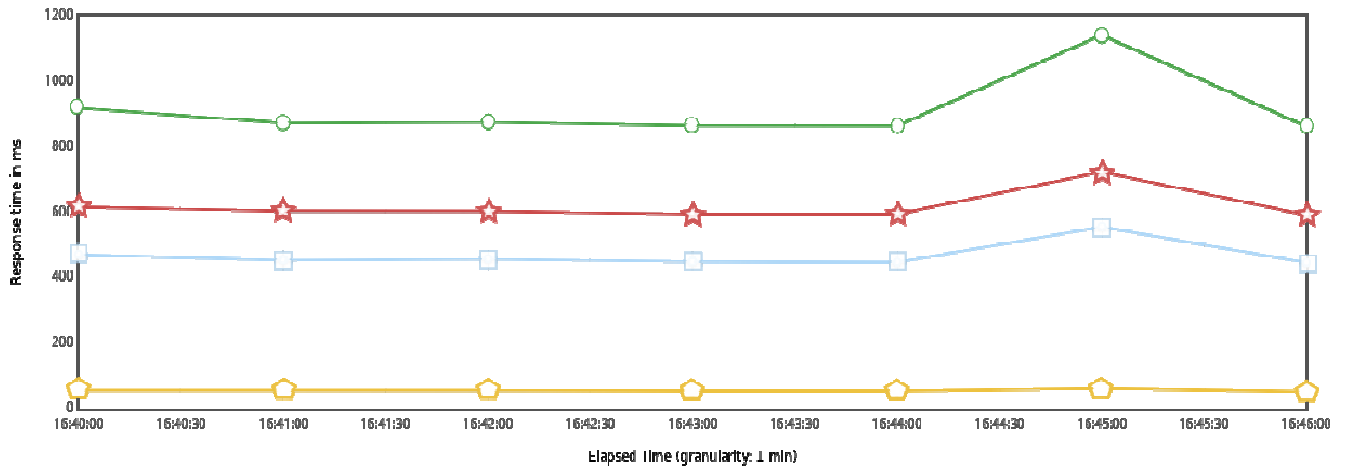


FIGURE 9. Results of the stress tests. The X axis represents the total elapsed time of the executed test, the Y axis represents the response time in milliseconds. The first line, from above (circles), represents the calls to the “login” endpoint. The second one (stars), represents the calls to the “add_action” endpoint. The next one (squares), represents the calls to the “add_measure” endpoint. The last one (rhombuses), in bottom, represents the calls to the home page of the API, this chart is showed as a representation of the minimum computable time in which the RAI takes to process a basic user request.

Once all the above information is on the central repository, an activity recognition module can be run with the aim of identifying (among many others) the Watching TV activity. In this case, the central point resides in the timestamp and location fields of the LEAs data objects: if they overlap all together, then there is a certainty that the elderly is watching TV.

The steps illustrated above demonstrate the goals of the Personal Data Capturing System and how it can feed the upper layers of the City4Age platform. Starting from raw data coming from heterogeneous devices, each with its own technologies and data formats, the LEBB module installed on the gateway (being it a smartphone or a home gateway) creates a proper LEA, inserting information with a high level of abstraction, independent of any low-level technology. Then the Common Data Format object is sent to the DSMS, from where further actions can be performed.

B. DATA STORE AND MANAGEMENT SYSTEM VALIDATION

For the low-level validation, a stress based test has been performed to demonstrate that the proposed architecture is capable of handling multiple connections from multiple instances of the IoT middleware. To perform it, we have used Apache Jmeter.²¹ This tool simulates different users (middleware) connecting to the RAI in a set of different time intervals. We have simulated a high demand scenario, with a high volume of data and multiple connections from different sources in order to test its reliability in a Smart City deployment.

In the performed test we simulated 800 middleware instances sending information in an interval of 0.5 seconds. During the test, we had at least 4 active users per second making in overall 8 hits per second to the RAI. Each middleware sends 4 different requests to the RAI;

- 1) A GET request to the main page of the RAI that returns a status code of 200 with a simple HTML code that contains a welcome page;
- 2) a POST request where the middleware sends a login credentials to be authenticated in the RAI, if the credentials are correct, the RAI returns a status code of 200 with an encrypted cookie and token;
- 3) a POST request where the user sends a list of 12 JSON instances of “add_action” to be stored into database, if data is stored successfully the RAI returns an status code of 200 with a confirmation message;
- 4) a POST request where the middleware sends a list of 12 JSON instances of “add_measure” to be stored into database, if the data is stored successfully it returns an status code of 200 with a confirmation message.

The simulation environment was a dedicated server that uses an Intel(R) Xeon(R) based processor (E5606) at 2.1Ghz of clock speed, with 8GB of RAM memory at 1333Mhz clock speed using a dual channel technology and a 500GB ATA disk with a maximum speed ratio at 300MB/s with 7200 nominal media rotation rate.

Fig. 9 depicts the results obtained in the test. It took 6 minutes to be completed without any errors (the response code from the RAI was 200 in all situations). As can be seen in the figure, the first line (the line bellow with rhombus) represents the GET request to the main page of the API. The reason of doing this is because it can be used as a reference value to know the minimum time that the RAI requires to respond to a single call. This request can be used as a basic reference for the rest of the requests. The “login” endpoint (the line above with circles) gives the biggest response time compared with the other requests. The result is reasonable knowing that the login process is very complex because the RAI needs to accept the middleware credentials and create the encrypted cookie in the call. This process consumes more resources that other requests and the impact is showed in the response time of the chart. In average, the response time took

²¹<http://jmeter.apache.org/>

TABLE 2. Statistical results of stress test.

REST method	Execution			Response times (ms)							Network (KB/sec)	
Label	Samples	KO	Error	Average	Min	Max	90 th pct	95 th pct	99 th pct	Throughput	Recv	Sent
<i>Home Page</i>	800	0	0.00%	51.60	33	305	61.00	70.95	157.86	2.00	3.90	0.91
<i>Login</i>	800	0	0.00%	914.40	848	2184	983.90	1199.15	1766.91	1.99	1.31	0.55
<i>Add_action</i>	800	0	0.00%	621.47	563	1508	684.90	790.85	113.92	2.00	1.10	11.22
<i>Add_measure</i>	800	0	0.00%	471.46	432	1184	517.00	590.95	874.94	2.00	1.13	13.11
Total	3200	0	0.00%	514.73	33	2184	874.00	916.00	1317.00	7.94	7.40	25.66

The above table contains the statistical metrics obtained in the stress test. The test simulates 800 different middleware instances sending information to the RAI. The last row contains the total data captured during the test. Other rows show the individual data captured for each method executed into the RAI. The statistical response times are calculated based on the successfully response (200 OK) when the RAI gives a call back the request.

around 914ms, but this endpoint is used only once, when the middleware instance needs to verify the user credentials and create the needed access token. The “*add_action*” (stars) and “*add_measure*” (squares), which are the main endpoints to store data, are fast enough to demonstrate that the RAI is capable of handling multiple connections from different sources and store data in a reasonable time. According to the obtained results, we can see that the server is working as expected and it is giving valid results considering that the used dedicated server it is not fully prepared to be used in a real environment.

Table 2 contains detailed statistics of the performed test. The results obtained in overall reveal that the maximum response time of the process is 2184 milliseconds for the login process and the minimum one is for basic call to the home page that is 33 milliseconds. Using the average calculations of the test and subtracting the values calculated from the basic GET call to the home page of the RAI we can calculate the average response time that the RAI takes to process each different added value (that in general terms it takes longer than a simple GET). Thus, we can confirm that the RAI took an average of 569.87 milliseconds to process internally the *add_action* data samples and 419.86 milliseconds to process internally the *add_measure* data samples.

The overall speed obtained in this test confirms that the RAI is capable of manipulating a high volume of data from the different IoT middleware instances and responds in an acceptable period of time to provide a reliable and stable storage system in the Cloud.

VIII. HIGH LEVEL VALIDATION

The Madrid pilot consists of two main components, namely the mobile application (acting as a LEA) and the local pilot repository (acting as a CBB). Advanced versions of these components have been deployed and have produced the initial sets of pilot participants’ real data that already feed the City4Age Shared Repository and dashboards, where the data is analyzed and processed in order to obtain geriatric factors, and allows its visualization.

During the pilot, 20 participants are involved using the system for a long period of time (between 6 and 12 months). Recruited participants have been provided with already

pre-configured hardware needed to carry out the experiment (BLE Beacons, smartphone with the City4Age Madrid pilot application and a smart wristband). End-users personal data is fully protected and their privacy is secured. To this end, the Madrid pilot is compliant to the current and forthcoming EU regulations and to that national legislation framework for the personal data and privacy protection.

The aforementioned application gathers in real-time data, by using the mobile, originated on different built-in sensors and hardware such the IMU, GPS, Bluetooth and Wi-Fi. All this data sources produce raw data that is processed by the application itself taking advantage of the mobile’s processing capabilities. This initial preprocessing allows to contextualize the raw data and interpret it, hence giving it a meaning and also, being prepared for a second simple statistical analysis also performed within the mobile device. These two processes output LEAs and Measures. All these LEAs and Measures are related to one (or more) geriatric factors and subfactors. This way, raw data coming from sensor devices can be transformed into meaningful geriatric data that allows behavioral interpretation, and are sent to the shared repository within a uniform format represented by the CDF.

Table 3 shows the data collected in the Madrid pilot in terms of LEAs and Measures and their related geriatric factors and sub-factors.

All this information gathered through the pilot application and devices is sent to the Madrid local pilot repository, where it is kept a backup copy of the data. All data collected is uploaded periodically (typically daily) to the City4Age central repository within the DSMS. In this way, by automatizing the process of data gathering through unobtrusive technologies, it is possible to obtain data directly related to proper geriatric factors, allowing a fast, scalable and automatic risk detection of elderly people.

The aim of this high level validation is also to evaluate if all the designed capturing systems are effective for collecting the elderly users’ behavior. Many threats, in fact, can pollute the data collecting phase, hence distorting the risk profile of the user. Leaving aside aspects related to the efficacy of the low level technologies, the main critical issue is related to the portability of the smartphone and wearable devices. Users, in fact, could forget to wear the

TABLE 3. LEAs and measures used in the Madrid pilot site.

Geriatric Factors	Geriatric Sub-factors	LEAs	Measures
Motility	Walking	BODY_STATE_START BODY_STATE_IN BODY_STATE_STOP state_type: Walking	WALK_DISTANCE WALK_SPEED_OUTDOOR WALK_STEPS WALK_TIME_OUTDOOR
	Still/moving	BODY_STATE_START BODY_STATE_STOP state_type: Still	STILL_TIME
Basic activities of daily living	Going out	POI_ENTER POI_EXIT location_type: Home	HOME_TIME OUTDOOR_NUM OUTDOOR_TIME
Instrumental activities of daily living	Shopping	POI_ENTER POI_EXIT location_type: Shop	SUPERMARKET_TIME SUPERMARKET_VISITS
	Transportation	TRANSPORT_ENTER TRANSPORT_EXIT location_type: PublicTransportationMean.Bus TRANSPORT_ENTER TRANSPORT_EXIT location_type: TransportationMean.Other	PUBLICTRANSPORT_DISTANCE_MONTH PUBLICTRANSPORT_RIDES_MONTH PUBLICTRANSPORT_TIME TRANSPORT_TIME
Socialization	Paying/receiving visits	POI_ENTER POI_EXIT location_type: SocializingPlace.FriendHome POI_ENTER POI_EXIT location_type: SocializingPlace.FamilyMemberHome	OTHERSOCIAL_TIME OTHERSOCIAL_TIME_OUT_PERC OTHERSOCIAL_VISITS
	Attending senior centers	POI_ENTER POI_EXIT location_type: SocializingPlace.SeniorCenter	SENIORCENTER_TIME SENIORCENTER_TIME_OUT_PERC SENIORCENTER_VISITS SENIORCENTER_VISITS_MONTH
	Attending other social places	POI_ENTER POI_EXIT location_type: SocializingPlace.PublicPark POI_ENTER POI_EXIT location_type: SocializingPlace.OtherSocialPlace	OTHERSOCIAL_TIME OTHERSOCIAL_TIME_OUT_PERC OTHERSOCIAL_VISITS PUBLICPARK_TIME PUBLICPARK_VISITS_MONTH PUBLICPARK_VISITS
Cultural engagement	Visiting cultural or entertainment places	POI_ENTER POI_EXIT location_type: CulturalPlace	CULTUREPOI_VISITS_MONTH CULTUREPOI_VISITS_TIME_PERC_MONTH

wristband or to carry always with them the smartphone when they go outside, and this would imply a bias towards a “too sedentary” value of the users’ risk profile, despite a potentially healthy lifestyle. Another issue is related to devices’ power consumptions. Beacons, wristbands, smartphones are

battery-powered devices whose charge level should be frequently checked, to avoid the total battery discharge and compromising the related data collection due to device shutdown.

These are only few examples of real use case scenarios that can pollute the data collection. As it can be seen, there is a concrete risk of under-estimating the behavioral profile of the users, but if it represents a systematic error, it can be properly identified and corrected.

IX. DISCUSSION ON A COMPARATIVE ANALYSIS

In this Section, a brief qualitative comparison among the City4Age project and other similar research projects is carried out. Given the extent of the context in which these works are framed, it is not possible to follow general guidelines to perform an objective comparison. Therefore, the rationale behind this, it is to identify if and how the considered research projects fulfil the main features addressed by the City4Age Project. They are mainly related to the following perspectives: final user empowerment, technology and data modeling features, affordability of the sensing architecture and domain experts’ involvement.

Focusing on AAL research, the early detection of frailty and MCI has revealed as important steps to effectively promote active and healthy ageing initiatives. Many developments were done in this area, promoting personalized interventions based on preventive and predictive solutions (PreventIT,²² FrailSafe,²³ Nestore).²⁴ As consequence, user empowerment is a common concept in most of these projects, allowing users to shed their passive role and play an active part in the decision-making process about their lifestyle, health and quality of life.

To do so, solutions should provide continuous monitoring of users, in order to provide analysis or prediction of the location of a user, to behavior or health status recognition of an occupant living at home. Very common solution is providing embedded systems. These are not necessarily embedded in the residence or building structure (Smart City Odense,²⁵ Mario,²⁶ Habitat), but are designed for indoor use and include wearable sensors to detect changes in vital signs (NITICS²⁷; FrailSafe; Habitat).²⁸

In fact, the usage of wearable devices is very extended, because of the importance of providing less obtrusive monitoring with AAL paradigm. The use of wearable sensors networks provides much better scalability, flexibility and inexpensiveness respect to conventional approaches, but they are still designed for home/indoor use (FrailSafe, Nestore, PreventIT, NITICS, Habitat).

AAL projects claim for active and healthy ageing taking place within the context of friends, work, neighborhoods

²²<http://www.preventit.eu/>

²³<https://frailsafe-project.eu/>

²⁴http://cordis.europa.eu/project/rcn/211703_es.html

²⁵<https://www.odense.dk/byens-udvikling/smart-city>

²⁶<http://www.mario-project.eu/portal/>

²⁷<http://www.aal-europe.eu/projects/nitics/>

²⁸<http://www.eng.habitatproject.info/project>

and family, in many different environments (home, leisure spaces, work, transportation, city in the end). In order to do so, solutions must transition from homes to cities. Internet of Things paradigm contribute to this transition.

With regard to the Internet of Things paradigm, one of the main advantages that it offers is interoperability. In that sense, as technology evolves and new sources of information arise, new solutions must contemplate the scalability of their systems allowing data aggregation and modularity to adapt them. A first approach for the definition of tomorrows' Smart Cities is to enhance data acquisition process with a logical level, where raw data acquisition adds and aggregates value of interpretation. The previously mentioned theory of evidence is a first approach to introduce a semantic meaning to acquired data and is being promoted in projects such as SCRIBE,²⁹ Smart Santander³⁰ or Smart City Odense³¹ being a step ahead of ad hoc solutions, mainly based on embedded technology such as NITICS. The next step is to elevate this semantic to the ontology level, which enables interoperability and flexibility among multiple smart city data sources, and provides functional services adapted to the user.

On another level, it must be evaluated if the technologies offered are affordable for the elderly population. In some cases, the research is based on technologies that are currently not affordable for the average population income, but that in the near future are expected to reduce their cost. City4Age relies on everyday technology currently established in Western societies; creation of new applications aimed at the elderly population also supposes support for the inclusion and motivation of the use of these technologies by this sector of the population [36]. Finally, it integrates the role of elderly citizen in a well-extended market with a set of infrastructures already available, although location services such as commercial GPS and GSM networks are not accurate enough to support indoor localization (alternative systems increase the cost of the solutions in over thousands of euros).

Despite defending the important role and benefit of a strategy based on aggregation, interoperability, continuous and unobstructed monitoring of data in smart cities, the specialization in the interpretation of these data supposes a final competitive difference. As discussed in the Section VIII, a solid interpretation foundation based on the opinion of an expert, as the geriatric factors used in City4Age, gives a final value to the solution without penalizing the features previously highlighted.

It is also common to find cases in which the design flows in the opposite direction. For example, the search to automate the dependency models already in place (such as the AGGIR model of the French hospital framework). Another example would be the extension of the HOPE³² project, within Smart City Odense initiative, that proposes a solution in the home

TABLE 4. Comparison among City4Age and similar research projects.

	User empowerment	Based on city-embedded technology	Based on Portable technology	Unobtrusive monitoring	Relies on theory of evidence	Multi agent system	Inexpensive solution	Predictive or trend modelling	Allow the use of Ontologies	Easy to replicate	Based on expert solutions (geriatric factors)
MARIO		x		x				x			
myAHA	x				x					x	X
NESTORE	x	x		x		x		x	x	x	
REACH				x	x	x		x			X
PreventIT			x	x		x	x	x			x
FrailSafe	x	x	x	x	x	x		x	x		X
NITICS	x	x		x	x	x				x	
HABITAT		x		x	x	x					x
Smart City Odense	x	x				x		x			x
City4Age	x	x	x	x	x	x	x	x	x	x	x

for the detection of Alzheimer disease. These examples reveal the need for systems, such as the one proposed, to extend automated solutions based on expert models to the city environment. In this sense, City4Age reveals as a bridge between current indoor Ambient Assisted solutions (see Table 4) and age-friendly cities.

X. CONCLUSIONS

This work presents a Smart City oriented infrastructure for unobtrusively collecting and managing data related to elderly people behavior patterns. The infrastructure, developed within the City4Age project, combines the Internet of Things and Linked Open Data paradigms to provide a scalable and responsive system able to provide services to multiple Cities concurrently. This infrastructure allows Cities to integrate their data on different abstraction levels, providing a semantic endpoint that offers an expressive data format for inference and querying purposes. Based on this information, complex risk detection algorithms can be performed in order to early identify potential treats related to the onset of frailty or MCI.

Currently, the proposed system is being deployed in six Cities (Lecce, Madrid, Montpellier, Athens, Birmingham and Singapore), part of the City4Age pilot sites, with the aim of verifying the correct flow of gathered data and assessing the usefulness of these data for domain experts (mainly geriatricians) to empower and validate their work.

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²⁹http://researcher.watson.ibm.com/researcher/view_group.php?id=2505

³⁰<http://www.smartsantander.eu/>

³¹<https://www.odense.dk/byens-udvikling/smart-city>

³²<http://www.hope-project.eu/>

REFERENCES

- [1] M. L. Stefanizzi, L. Mottola, L. Mainetti, and L. Patrono, "COIN: Opening the internet of things to people's mobile devices," *IEEE Commun. Mag.*, vol. 55, no. 2, pp. 20–26, Feb. 2017.
- [2] L. Mainetti, V. Mighali, and A. L. Patrono, "A software architecture enabling the Web of Things," *IEEE Internet Things J.*, vol. 2, no. 6, pp. 445–454, Jun. 2015.
- [3] L. Catarinucci et al., "An IoT-aware architecture for smart healthcare systems," *IEEE Internet Things J.*, vol. 2, no. 6, pp. 515–526, Dec. 2015.
- [4] L. Mainetti, L. Manco, L. Patrono, A. Secco, I. Sergi, and R. Vergallo, "An ambient assisted living system for elderly assistance applications," in *Proc. IEEE 27th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Valencia, Spain, Sep. 2016, pp. 1–6.
- [5] S. Bandyopadhyay, M. Sengupta, S. Maiti, and S. Dutta, "Role of middleware for internet of things: A study," *Int. J. Comput. Sci. Eng. Survey*, vol. 2, no. 3, pp. 94–105, 2011.
- [6] M. A. Hossain, J. Parra, S. M. M. Rahman, A. Alamri, S. Ullah, and H. T. Mouftah, "From sensing to alerting: A pathway of RESTful messaging in ambient assisted living," *IEEE Wireless Commun.*, vol. 23, no. 2, pp. 102–110, Apr. 2016.
- [7] Z. Ji, I. O. Ganchev, M. Droma, L. Zhao, and X. Zhang, "A cloud-based car parking middleware for IoT-based smart cities: Design and implementation," *Sensors*, vol. 14, no. 12, pp. 22372–22393, 2014.
- [8] A. Gómez-Goiri, P. Orduña, J. Diego, and D. López-De-Ipiña, "Otsopack: Lightweight semantic framework for interoperable ambient intelligence applications," *Comput. Hum. Behav.*, vol. 30, pp. 460–467, Jan. 2014.
- [9] A. Almeida and D. López-De-Ipiña, "A distributed reasoning engine ecosystem for semantic context-management in smart environments," *Sensors*, vol. 12, no. 8, pp. 10208–10227, 2012.
- [10] F. Latfi and B. Lefebvre, C. Descheneaux, "Ontology-based management of the telehealth smart home, dedicated to elderly in loss of cognitive autonomy," in *Proc. OWLED Workshop OWL, Exper. Directions*, 2007, pp. 1–10. [Online]. Available: http://www.webont.org/owled/2007/PapersPDF/submission_37.pdf
- [11] M. Klein, A. Schmidt, and R. Lauer, "Ontology-centred design of an ambient middleware for assisted living: The case of SOPRANO," in *Proc. Towards Ambient Intell., Methods Cooperat. Ensembles Ubiquitous Environ. (AIM-CU) 30th Annu. German Conf. Artif. Intell. (KI)*, Osnabrück, Germany, 2007, pp. 1–8.
- [12] *The EU SOPRANO IP Project*. Accessed: Jan. 26, 2018. [Online]. Available: http://cordis.europa.eu/project/rcn/80527_en.html
- [13] L. Chen, C. Nugent, M. Mulvenna, D. Finlay, and X. Hong, "Semantic smart homes: Towards knowledge rich assisted living environments," in *Intelligent Patient Management (Studies in Computational Intelligence)*, vol. 189, S. McClean, P. Millard, E. El-Darzi, and C. Nugent, Eds. Berlin, Germany: Springer, 2009, pp. 279–296.
- [14] D. López-De-Ipiña et al., "EMI²lets: A reflective framework for enabling Aml," *J. Universal Comput. Sci.*, vol. 12, no. 3, pp. 297–314, 2006.
- [15] A. Krylovskiy, M. Jahn, and E. Patti, "Designing a smart city internet of things platform with microservice architecture," in *Proc. 3rd Int. Conf. Future Internet Things Cloud (FiCloud)*, Aug. 2015, pp. 25–30.
- [16] A. Azzara, S. Bocchino, P. Pagano, G. Pellerano, and M. Petracca, "Middleware solutions in WSN: The IoT oriented approach in the ICSI project," in *Proc. 21st Int. Conf. Softw., Telecommun. Comput. Netw. (SoftCOM)*, Sep. 2013, pp. 1–6.
- [17] E. Theodoridis, G. Mylonas, and I. Chatzigiannakis, "Developing an IoT smart city framework," in *Proc. 4th Int. Conf. Inf., Intell., Syst. Appl. (IISA)*, Jul. 2013, pp. 1–6.
- [18] K. E. Skouby, A. Kivimäki, L. Haukiputo, P. Lynggaard, and I. Windekilde, "Smart cities and the ageing population," in *Proc. 32nd Meeting WWRF*, 2014, pp. 1–12.
- [19] I. Azimi, A. M. Rahmani, P. Liljeberg, and H. Tenhunen, "Internet of things for remote elderly monitoring: A study from user-centered perspective," *J. Ambient Intell. Humanized Comput.*, vol. 8, no. 2, pp. 273–289, Jun. 2016.
- [20] P. Kumari, L. Mathew, and P. Syal, "Increasing trend of wearables and multimodal interface for human activity monitoring: A review," *Biosensors Bioelectron.*, vol. 90, pp. 298–307, Apr. 2017.
- [21] G. Shafer, *A Mathematical Theory of Evidence*, vol. 1. Princeton, NJ, USA: Princeton Univ. Press, 1976.
- [22] A. P. Dempster, "A generalization of Bayesian inference," in *Classic works Dempster-Shafer Theory Belief Functions (Studies in Fuzziness and Soft Computing)*, vol. 219, R. R. Yager and L. Liu, Eds. Berlin, Germany: Springer, 2008, pp. 73–104.
- [23] A. Gaur, B. Scotney, G. Parr, and S. McClean, "Smart city architecture and its applications based on IoT," *Procedia Comput. Sci.*, vol. 52, pp. 1089–1094, Jan. 2015.
- [24] P. Paolini, N. Di Blas, S. Copelli, and F. Mercalli, "Health prevention for the aging population in smart cities: The City4Age project," in *Proc. IEEE 3rd Int. Forum Res. Technol. Soc. Ind. (RTSI)*, Sep. 2017, pp. 1–6.
- [25] L. Mainetti, L. Patrono, and P. Rametta, "Capturing behavioral changes of elderly people through unobtrusive sensing technologies," in *Proc. 24th Int. Conf. Softw., Telecommun. Comput. Netw. (SoftCOM)*, Split, Croatia, 2016, pp. 1–3.
- [26] R. Mulero et al., "An AAL system based on IoT technologies and linked open data for elderly monitoring in smart cities," in *Proc. 2nd Int. Multidisciplinary Conf. Comput. Energy Sci. (SpliTech)*, Split, Croatia, Jul. 2017, pp. 1–6.
- [27] R. Mulero, A. Almeida, L. Patrono, P. Rametta, and I. Sergi, "An innovative approach for elderly behavioral analysis by adopting enabling IoT technologies," in *Proc. 25th Int. Conf. Softw., Telecommun. Comput. Netw. (SoftCOM)*, Split, Croatia, Sep. 2017, pp. 1–6.
- [28] A. Caione, A. Fiore, L. Mainetti, L. Manco, and R. Vergallo, "WoX: Model-driven development of Web of things applications," in *Managing the Web of Things*, B. B. Quan, Z. Sheng, Y. Qin, L. Yao, Eds. Amsterdam, The Netherlands: Elsevier, 2017, pp. 357–387.
- [29] L. Mainetti, L. Manco, L. Patrono, I. Sergi, and R. Vergallo, "Web of topics: An IoT-aware model-driven designing approach," in *Proc. IEEE World Forum Internet Things (WF-IoT)*, Milan, Italy, Dec. 2015, pp. 46–51, doi: [10.1109/WF-IoT.2015.7389025](https://doi.org/10.1109/WF-IoT.2015.7389025).
- [30] L. Mainetti, V. Mighali, L. Patrono, P. Rametta, and M. L. Stefanizzi, "An IoT-aware system for elderly monitoring," in *Proc. IEEE 3rd Int. Forum Res. Technol. Soc. Ind. (RTSI)*, Modena, Italy, Sep. 2017, pp. 1–5.
- [31] L. Patrono, P. Primiceri, P. Rametta, I. Sergi, and P. Visconti, "An innovative approach for monitoring elderly behavior by detecting home appliance's usage," in *Proc. 25th Int. Conf. Softw., Telecommun. Comput. Netw. (SoftCOM)*, Split, Croatia, Sep. 2017, pp. 1–7.
- [32] N. Provos, D. Mazières, and T. J. Sutton, "A future-adaptable password scheme," in *Proc. USENIX Annu. Tech. Conf.*, 1999, pp. 81–92.
- [33] J. Daemen and V. Rijmen, *The Design of Rijndael AES—The Advanced Encryption Standard*, vol. 17, J. Daemen and V. Rijmen, Eds. Berlin, Germany: Springer, 2002, p. 238.
- [34] A. Almeida and G. Azkune, "Activity recognition approaches for smart cities: The City4Age use case," in *Proc. IEEE 3rd Int. Forum Res. Technol. Soc. Ind. (RTSI)*, Sep. 2017, pp. 1–5.
- [35] P. Orduña, A. Almeida, U. Aguilera, X. Laiseca, D. López-De-Ipiña, and A. G. Goiri, "Identifying security issues in the semantic Web: Injection attacks in the semantic query languages," *Actas VI Jornadas Científico-Técnicas en Servicios Web y (SOA)*, vol. 51, pp. 4529–4542, Sep. 2010.
- [36] R. Mcgaughey, S. Zeltmann, and M. McMurtrey, "Motivations and obstacles to smartphone use by the elderly: Developing a research framework," *Int. J. Electron. Finance*, vol. 7, nos. 3–4, pp. 177–195, 2013.



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